

6. Appendix

6.1. Closed-form computation of uncertainty measures & Uncertainty attacks

Dirichlet-based uncertainty models allow to compute several uncertainty measures in closed form (see (Malinin & Gales, 2018a) for a derivation). As proposed by (Malinin & Gales, 2018a), we use precision m_{α_0} , differential entropy m_{diffE} and mutual information m_{MI} to estimate uncertainty on predictions.

The differential entropy m_{diffE} of a DBU model reaches its maximum value for equally probable categorical distributions and thus, a on flat Dirichlet distribution. It is a measure for distributional uncertainty and expected to be low on ID data, but high on OOD data.

$$m_{\text{diffE}} = \sum_c^K \ln \Gamma(\alpha_c) - \ln \Gamma(\alpha_0) - \sum_c^K (\alpha_c - 1) \cdot (\Psi(\alpha_c) - \Psi(\alpha_0)) \quad (7)$$

where α are the parameters of the Dirichlet-distribution, Γ is the Gamma function and Ψ is the Digamma function.

The mutual information m_{MI} is the difference between the total uncertainty (entropy of the expected distribution) and the expected uncertainty on the data (expected entropy of the distribution). This uncertainty is expected to be low on ID data and high on OOD data.

$$m_{\text{MI}} = - \sum_{c=1}^K \frac{\alpha_c}{\alpha_0} \left(\ln \frac{\alpha_c}{\alpha_0} - \Psi(\alpha_c + 1) + \Psi(\alpha_0 + 1) \right) \quad (8)$$

Furthermore, we use the precision α_0 to measure uncertainty, which is expected to be high on ID data and low on OOD data.

$$m_{\alpha_0} = \alpha_0 = \sum_{c=1}^K \alpha_c \quad (9)$$

As these uncertainty measures are computed in closed form and it is possible to obtain their gradients, we use them (i.e. m_{diffE} , m_{MI} , m_{α_0}) are target function of our uncertainty attacks. Changing the attacked target function allows us to use a wide range of gradient-based attacks such as FGSM attacks, PGD attacks, but also more sophisticated attacks such as Carlini-Wagner attacks.

6.2. Details of the Experimental setup

Models. We trained all models with a similar based architecture. We used namely 3 linear layers for vector data sets, 3 convolutional layers with size of 5 + 3 linear layers for

MNIST and the VGG16 (Simonyan & Zisserman, 2015) architecture with batch normalization for CIFAR10. All the implementation are performed using Pytorch (Paszke et al., 2019). We optimized all models using Adam optimizer. We performed early stopping by checking for loss improvement every 2 epochs and a patience of 10. The models were trained on GPUs (1 TB SSD).

We performed a grid-search for hyper-parameters for all models. The learning rate grid search was done in $[1e^{-5}, 1e^{-3}]$. For PostNet, we used Radial Flows with a depth of 6 and a latent space equal to 6. Further, we performed a grid search for the regularizing factor in $[1e^{-7}, 1e^{-4}]$. For PriorNet, we performed a grid search for the OOD loss weight in $[1, 10]$. For DDNet, we distilled the knowledge of 5 neural networks after a grid search in $[2, 5, 10, 20]$ neural networks. Note that it already implied a significant overhead at training compare to other models.

Metrics. For all experiments, we focused on using AUC-PR scores since it is well suited to imbalance tasks (Saito & Rehmsmeier, 2015) while bringing theoretically similar information than AUC-ROC scores (Davis & Goadrich, 2006). We scaled all scores from $[0, 1]$ to $[0, 100]$. All results are average over 5 training runs using the best hyper-parameters found after the grid search.

Data sets. For vector data sets, we use 5 different random splits to train all models. We split the data in training, validation and test sets (60%, 20%, 20%).

We use the segment vector data set (Dua & Graff, 2017), where the goal is to classify areas of images into 7 classes (window, foliage, grass, brickface, path, cement, sky). We remove class window from ID training data to provide OOD training data to PriorNet. Further, We remove the class 'sky' from training and instead use it as the OOD data set for OOD detection experiments. Each input is composed of 18 attributes describing the image area. The data set contains 2,310 samples in total.

We further use the Sensorless Drive vector data set (Dua & Graff, 2017), where the goal is to classify extracted motor current measurements into 11 different classes. We remove class 9 from ID training data to provide OOD training data to PriorNet. We remove classes 10 and 11 from training and use them as the OOD dataset for OOD detection experiments. Each input is composed of 49 attributes describing motor behaviour. The data set contains 58,509 samples in total.

Additionally, we use the MNIST image data set (LeCun & Cortes, 2010) where the goal is to classify pictures of hand-drawn digits into 10 classes (from digit 0 to digit 9). Each input is composed of a $1 \times 28 \times 28$ tensor. The data set contains 70,000 samples. For OOD detection experiments, we use FashionMNIST (Xiao et al., 2017) and KMNIST

(Clanuwat et al., 2018) containing images of Japanese characters and images of clothes, respectively. FashionMNIST was used as training OOD for PriorNet while KMNIST is used as OOD at test time.

Finally, we use the CIFAR10 image data set (Krizhevsky et al., 2009) where the goal is to classify a picture of objects into 10 classes (airplane, automobile, bird, cat, deer, dog, frog, horse, ship, truck). Each input is a $3 \times 32 \times 32$ tensor. The data set contains 60,000 samples. For OOD detection experiments, we use street view house numbers (SVHN) (Netzer et al., 2011) and CIFAR100 (Krizhevsky et al., 2009) containing images of numbers and objects respectively. CIFAR100 was used as training OOD for PriorNet while SVHN is used as OOD at test time.

Perturbations. For all label and uncertainty attacks, we used Fast Gradient Sign Methods and Project Gradient Descent. We tried 6 different attack radii $[0.0, 0.1, 0.2, 0.5, 1.0, 2.0, 4.0]$. These radii operate on the input space after data normalization. We bound perturbations by L_∞ -norm or by L_2 -norm, with

$$L_\infty(x) = \max_{i=1, \dots, D} |x_i| \quad \text{and} \quad L_2(x) = \left(\sum_{i=1}^D x_i^2 \right)^{0.5}. \quad (10)$$

For L_∞ -norm it is obvious how to relate perturbation size ε with perturbed input images, because all inputs are standardized such that the values of their features are between 0 and 1. A perturbation of size $\varepsilon = 0$ corresponds to the original input, while a perturbation of size $\varepsilon = 1$ corresponds to the whole input space and allows to change all features to any value.

For L_2 -norm the relation between perturbation size ε and perturbed input images is less obvious. To justify our choice for ε w.r.t. this norm, we relate perturbations size ε_2 corresponding to L_2 -norm with perturbations size ε_∞ corresponding to L_∞ -norm. First, we compute ε_2 , such that the L_2 -norm is the smallest super-set of the L_∞ -norm. Let us consider a perturbation of ε_∞ . The largest L_2 -norm would be obtained if each feature is perturbed by ε_∞ . Thus, perturbation ε_2 , such that L_2 encloses L_∞ is $\varepsilon_2 = (\sum_{i=1}^D \varepsilon_\infty^2)^{0.5} = \sqrt{D}\varepsilon_\infty$. For the MNIST-data set, with $D = 28 \times 28$ input features L_2 -norm with $\varepsilon_2 = 28$ encloses L_∞ -norm with $\varepsilon_\infty = 1$.

Alternatively, ε_2 can be computed such that the volume spanned by L_2 -norm is equivalent to the one spanned by L_∞ -norm. Using that the volume spanned by L_∞ -norm is ε_∞^D and the volume spanned by L_2 -norm is $\frac{\pi^{0.5D} \varepsilon_2^D}{\Gamma(0.5D+1)}$ (where Γ is the Gamma-function), we obtain volume equivalence if $\varepsilon_2 = \Gamma(0.5D+1)^{\frac{1}{D}} \sqrt{\pi} \varepsilon_\infty$. For the MNIST-data set, with $D = 28 \times 28$ input features L_2 -norm with $\varepsilon_2 \approx 21.39$ is volume equivalent to L_∞ -norm with $\varepsilon_\infty = 1$.

6.3. Additional Experiments

Table 8 and 9 illustrate that no DBU model maintains high accuracy under gradient-based label attacks. Accuracy under PGD attacks decreases more than under FGSM attacks, since PGD is stronger. Interestingly Noise attacks achieve also good performances with increasing Noise standard deviation. Note that the attack is not constraint to be with a given radius for Noise attacks.

Table 8. Accuracy under PGD label attacks.

Att. Rad.	0.0	0.1	0.2	0.5	1.0	2.0	4.0	0.0	0.1	0.2	0.5	1.0	2.0	4.0
MNIST														
PostNet	99.4	99.2	98.8	96.8	89.6	53.8	13.0	89.5	73.5	51.7	13.2	2.2	0.8	0.3
PriorNet	99.3	99.1	98.8	97.4	93.9	75.3	4.8	88.2	77.8	68.4	54.0	37.9	17.5	5.1
DDNet	99.4	99.1	98.8	97.5	91.6	48.8	0.2	86.1	73.9	59.1	20.5	1.5	0.0	0.0
EvNet	99.2	98.9	98.4	96.8	92.4	73.1	40.9	89.8	71.7	48.8	11.5	2.7	1.5	0.4
Sensorless														
PostNet	98.3	13.1	6.4	4.0	7.0	9.8	11.3	98.9	82.8	50.1	19.2	8.8	5.1	8.6
PriorNet	99.3	16.5	5.6	1.2	0.4	0.2	1.6	99.5	90.7	47.6	7.8	0.2	0.0	0.4
DDNet	99.3	12.4	2.4	0.6	0.3	0.1	0.1	99.2	90.8	45.7	6.9	0.0	0.0	0.0
EvNet	99.0	35.3	22.3	11.2	7.0	5.2	4.0	99.3	91.8	54.0	10.3	0.8	0.5	0.6

Table 9. Accuracy under FGSM label attacks.

Att. Rad.	0.0	0.1	0.2	0.5	1.0	2.0	4.0	0.0	0.1	0.2	0.5	1.0	2.0	4.0
MNIST														
PostNet	99.4	99.2	98.9	97.7	95.2	90.1	79.2	89.5	72.3	54.9	31.2	21.0	16.8	15.6
PriorNet	99.3	99.1	98.9	97.7	95.8	93.2	76.7	88.2	77.3	70.1	59.4	52.3	48.5	46.8
DDNet	99.4	99.2	98.9	97.8	94.7	79.2	25.2	86.1	73.0	60.2	32.5	14.6	7.1	6.0
EvNet	99.2	98.9	98.6	97.6	95.8	90.1	74.4	89.8	71.4	54.5	29.6	18.1	14.4	13.4
Sensorless														
PostNet	98.3	19.6	10.9	10.9	11.9	12.4	12.5	98.9	79.6	57.3	31.5	18.4	20.6	19.9
PriorNet	99.3	24.7	11.8	8.6	8.5	8.1	8.3	99.5	85.5	40.5	8.9	0.4	0.3	0.2
DDNet	99.3	18.0	8.2	6.5	5.4	6.7	7.8	99.2	86.4	36.2	11.9	0.9	0.0	0.0
EvNet	99.0	42.0	28.0	17.5	13.7	13.6	14.9	99.3	90.6	55.2	14.2	2.4	0.5	0.1

Table 10. Accuracy under Noise label attacks.

Noise Std	0.0	0.1	0.2	0.5	1.0	2.0	4.0	0.0	0.1	0.2	0.5	1.0	2.0	4.0
MNIST														
PostNet	99.4	98.6	91.8	14.9	1.3	0.1	0.0	91.7	21.5	10.1	0.1	1.2	0.0	1.9
PriorNet	99.3	98.5	95.7	14.4	0.0	0.0	0.0	87.7	28.1	11.2	9.7	5.0	8.5	9.0
DDNet	99.4	98.6	92.4	13.3	0.7	0.0	0.0	81.7	23.0	11.2	11.2	11.0	7.8	6.7
EvNet	99.3	96.9	81.6	11.7	0.5	0.0	0.0	89.5	20.7	11.1	5.2	0.5	2.3	3.9
Sensorless														
PostNet	98.1	0.1	3.7	11.7	11.7	11.7	11.7	98.5	39.4	3.9	1.8	12.1	20.3	22.1
PriorNet	99.3	0.2	0.0	0.0	0.0	0.3	2.4	99.4	47.9	8.8	0.0	0.0	0.0	0.0
DDNet	99.0	0.4	0.1	0.0	0.0	0.0	0.0	99.1	50.0	10.3	0.0	0.0	0.3	0.0
EvNet	98.6	0.2	0.0	0.1	1.4	4.6	8.8	99.1	50.3	10.3	1.2	0.3	0.0	1.5

6.3.1. UNCERTAINTY ESTIMATION UNDER LABEL ATTACKS

Is low uncertainty a reliable indicator of correct predictions?

On non-perturbed data uncertainty estimates are an indicator of correctly classified samples, but if the input data is perturbed none of the DBU models maintains its high performance. Thus, uncertainty estimates are not a robust indicator of correctly labeled inputs.

Table 2, 11, 12, and 13 illustrate that neither differential entropy nor precision, nor mutual information are a reliable indicator of correct predictions under PGD attacks. DBU-models achieve significantly better results when they are attacked by FGSM-attacks (Table 14), but as FGSM attacks provide much weaker adversarial examples than PGD attacks, this cannot be seen as real advantage.

Table 15. Distinguishing between correctly and wrongly predicted labels based on the differential entropy under Noise label attacks (AUC-PR).

Noise Std	0.0	0.1	0.2	0.5	1.0	2.0	4.0		0.0	0.1	0.2	0.5	1.0	2.0	4.0
MNIST															
PostNet	99.9	99.8	99.6	74.2	7.4	0.2	0.0		98.7	76.3	24.3	0.4	4.9	0.0	1.7
PriorNet	99.9	99.9	99.8	73.4	0.0	0.0	0.0		85.0	27.8	15.9	20.4	7.0	7.7	8.3
DDNet	100.0	99.9	99.4	51.1	0.6	0.1	0.0		96.1	61.0	39.8	14.2	11.3	6.9	6.9
EvNet	99.5	98.4	88.5	20.2	0.9	0.0	0.0		97.5	66.1	21.4	7.7	2.3	3.0	3.8
Sensorless															
PostNet	99.7	0.3	3.2	13.3	12.0	11.7	11.7		99.9	53.9	4.8	1.8	11.2	21.7	21.6
PriorNet	100.0	0.3	0.0	0.0	0.0	7.8	11.5		100.0	84.5	15.6	0.0	0.0	0.0	0.0
DDNet	99.7	0.9	0.6	0.0	0.0	0.0	0.0		100.0	82.7	23.9	0.0	0.0	0.6	0.0
EvNet	99.8	0.3	0.0	0.1	1.7	5.5	10.0		100.0	78.3	19.0	3.5	0.5	0.0	1.7

Can we use uncertainty estimates to detect attacks against the class prediction?

PGD attacks do not explicitly consider uncertainty during the computation of adversarial examples, but they seem to provide perturbed inputs with similar uncertainty as the original input.

FGSM and Noise attacks are easier to detect, but also weaker than PGD attacks. This suggests that DBU models are capable of detecting weak attacks by using uncertainty estimation.

Table 16. Attack-Detection based on differential entropy under PGD label attacks (AUC-PR).

Att. Rad.	MNIST						Segment					
	0.1	0.2	0.5	1.0	2.0	4.0	0.1	0.2	0.5	1.0	2.0	4.0
PostNet	57.7	66.3	83.4	90.5	79.0	50.1	95.6	73.5	47.0	42.3	53.4	82.7
PriorNet	67.7	83.2	97.1	96.7	92.1	82.9	86.7	83.3	38.0	31.3	30.8	31.5
DDNet	53.4	57.1	68.5	83.9	96.0	86.3	76.1	83.5	45.4	32.4	30.8	30.8
EvNet	54.8	59.0	68.5	75.9	72.6	59.8	94.9	80.9	41.5	32.5	31.1	31.1

 Table 17. Attack-Detection based on precision α_0 under PGD label attacks (AUC-PR).

Att. Rad.	0.1	0.2	0.5	1.0	2.0	4.0	0.1	0.2	0.5	1.0	2.0	4.0
MNIST						CIFAR10						
PostNet	63.3	75.7	92.6	95.1	75.3	39.5	63.4	66.9	42.1	32.9	31.6	31.2
PriorNet	67.6	83.2	97.1	96.9	92.7	84.7	53.3	56.0	55.6	49.2	42.2	35.4
DDNet	52.7	55.7	64.7	78.4	91.9	80.9	55.8	60.5	57.3	38.7	32.3	31.4
EvNet	49.1	48.0	45.1	42.7	41.8	39.2	48.4	46.9	46.3	44.5	42.5	
Sensorless						Segment						
PostNet	39.8	35.8	35.4	52.0	88.2	99.0	94.6	70.3	46.3	42.6	54.9	84.0
PriorNet	40.9	35.1	32.0	31.1	30.7	30.7	82.7	82.6	39.4	31.6	30.8	30.8
DDNet	47.7	40.3	35.3	32.8	31.3	30.8	80.0	86.0	43.3	33.6	31.0	30.8
EvNet	45.4	39.7	36.1	34.8	34.7	36.0	90.9	72.4	40.4	32.4	31.1	31.1

Table 18. Attack-Detection based on mutual information under PGD label attacks (AUC-PR).

Att. Rad.	0.1	0.2	0.5	1.0	2.0	4.0	0.1	0.2	0.5	1.0	2.0	4.0
MNIST						CIFAR10						
PostNet	42.2	37.5	36.7	54.5	70.5	70.3	52.2	52.1	50.0	65.9	76.3	80.7
PriorNet	67.7	83.3	97.1	96.9	92.6	84.5	54.0	56.9	56.3	49.7	42.4	35.5
DDNet	53.1	56.3	66.5	81.0	94.0	82.9	56.0	60.8	57.4	38.2	32.1	31.3
EvNet	49.1	48.0	45.2	42.9	41.9	39.3	48.7	47.3	46.3	46.0	44.1	42.2
Sensorless						Segment						
PostNet	75.3	76.6	66.5	57.7	85.6	98.7	94.8	73.5	55.9	47.9	58.0	84.0
PriorNet	40.7	35.0	32.0	31.0	30.7	30.7	83.5	82.7	39.2	31.6	30.8	30.8
DDNet	48.0	40.0	35.2	32.6	31.2	30.8	82.4	88.1	43.4	33.4	30.9	30.8
EvNet	45.5	39.7	36.1	34.8	34.7	36.0	91.7	72.9	40.5	32.4	31.1	31.1

Table 19. Attack-Detection based on differential entropy under FGSM label attacks (AUC-PR).

Att. Rad.	0.1	0.2	0.5	1.0	2.0	4.0	0.1	0.2	0.5	1.0	2.0	4.0
MNIST						CIFAR10						
PostNet	55.9	61.8	74.8	84.0	88.9	89.9	62.1	67.2	65.7	63.1	65.4	73.8
PriorNet	67.4	82.4	96.9	98.3	98.9	99.6	58.4	63.1	68.5	70.1	68.5	62.5
DDNet	53.6	57.3	68.3	82.6	95.6	98.7	57.2	62.9	69.1	68.7	69.7	76.5
EvNet	54.1	57.4	63.8	67.6	68.6	69.9	57.8	61.7	63.3	62.9	65.7	72.5
Sensorless						Segment						
PostNet	98.4	99.8	99.9	99.9	99.9	99.9	96.9	93.9	99.5	99.9	100.0	100.0
PriorNet	48.7	38.6	32.7	32.9	38.6	44.3	89.0	80.8	46.7	37.2	33.7	32.4
DDNet	61.5	47.8	37.1	33.1	32.4	33.2	79.6	86.2	60.2	47.5	36.6	31.6
EvNet	67.3	65.5	72.3	73.4	75.3	79.1	95.7	87.2	59.3	51.7	51.1	53.5

Table 20. Attack-Detection based on differential entropy under Noise label attacks (AUC-PR).

Noise Std.	0.1	0.2	0.5	1.0	2.0	4.0	0.1	0.2	0.5	1.0	2.0	4.0
MNIST						CIFAR10						
PostNet	51.3	65.3	93.8	95.1	95.2	95.2	80.8	84.5	97.6	99.5	99.3	98.2
PriorNet	32.5	36.8	88.9	99.6	99.7	92.7	34.7	32.3	34.3	60.3	95.5	100.0
DDNet	60.7	87.6	99.8	100.0	99.9	99.8	59.1	62.6	81.5	98.6	99.8	98.7
EvNet	51.2	55.7	66.9	70.3	68.0	67.1	75.7	78.6	88.2	97.8	96.4	95.6
Sensorless						Segment						
PostNet	99.8	100.0	100.0	100.0	100.0	100.0	95.6	99.4	100.0	100.0	100.0	100.0
PriorNet	42.0	33.8	31.5	34.7	43.7	47.0	56.7	56.7	39.8	33.7	31.9	33.7
DDNet	53.4	43.5	34.3	31.6	32.5	36.1	57.0	58.9	43.1	33.7	31.5	31.3
EvNet	67.1	78.8	88.3	95.4	96.9	97.8	60.8	63.5	61.2	64.8	73.7	85.2

6.3.2. ATTACKING UNCERTAINTY ESTIMATION

Are uncertainty estimates a robust feature for OOD detection?

Using uncertainty estimation to distinguish between ID and OOD data is not robust as shown in the following tables.

Table 21. OOD detection based on differential entropy under PGD uncertainty attacks against differential entropy on ID data and OOD data (AUC-PR).

Att. Rad.	ID-Attack (non-attacked OOD)							OOD-Attack (non-attacked ID)						
	0.0	0.1	0.2	0.5	1.0	2.0	4.0	0.0	0.1	0.2	0.5	1.0	2.0	4.0
MNIST – KMNIST														
PostNet	94.5	94.1	93.9	91.1	77.1	44.0	31.9	94.5	93.1	91.4	82.1	62.2	50.7	48.8
PriorNet	99.6	99.4	99.1	97.8	93.8	77.6	32.0	99.6	99.4	99.1	98.0	94.6	85.5	73.9
DDNet	99.3	99.1	98.9	97.8	93.5	63.3	30.7	99.3	99.1	99.0	98.3	96.7	91.3	73.8
EvNet	69.0	67.1	65.6	61.8	57.4	50.9	43.6	69.0	55.8	48.0	39.4	36.2	34.9	34.4
Seg. – Seg. class sky														
PostNet	99.0	80.7	53.5	38.0	34.0	41.6	49.5	99.0	88.4	69.2	45.1	36.4	42.6	75.4
PriorNet	34.8	31.4	30.9	30.8	30.8	30.8	30.8	34.8	31.8	31.0	30.8	30.8	30.8	32.1
DDNet	31.5	30.9	30.8	30.8	30.8	30.8	30.8	31.5	31.0	30.8	30.8	30.8	30.8	30.8
EvNet	92.5	67.2	43.2	31.6	30.9	30.9	31.2	92.5	86.1	82.7	48.9	32.7	30.9	30.9

Table 22. OOD detection under PGD uncertainty attacks against differential entropy on ID data and OOD data (AUC-ROC).

Att. Rad.	ID-Attack (non-attacked OOD)							OOD-Attack (non-attacked ID)						
	0.0	0.1	0.2	0.5	1.0	2.0	4.0	0.0	0.1	0.2	0.5	1.0	2.0	4.0
MNIST – KMNIST														
PostNet	91.6	91.3	91.9	91.5	80.2	38.8	9.2	91.6	90.4	89.0	81.6	62.6	45.0	43.1
PriorNet	99.8	99.7	99.5	99.0	97.1	81.1	8.7	99.8	99.7	99.6	99.1	97.7	93.0	84.9
DDNet	99.2	98.9	98.6	97.3	92.1	58.2	1.2	99.2	99.0	98.8	97.9	95.8	89.1	69.3
EvNet	81.2	79.6	78.2	74.6	69.5	58.7	43.0	81.2	67.2	54.8	35.4	25.5	20.7	18.5
CIFAR10 – SVHN														
PostNet	87.0	71.9	56.3	30.2	20.2	15.0	9.7	87.0	71.0	54.3	33.5	30.3	26.2	19.4
PriorNet	62.4	48.2	35.9	13.8	3.6	0.9	0.3	62.4	48.0	35.6	14.8	6.6	3.4	1.6
DDNet	87.0	76.0	63.6	29.3	6.1	1.1	0.4	87.0	78.1	66.1	26.2	5.1	0.7	0.1
EvNet	88.0	69.1	51.7	24.6	15.5	9.5	4.2	88.0	72.0	60.7	47.9	42.1	33.3	24.0
Sens. – Sens. class 10, 11														
PostNet	85.3	49.1	38.1	7.8	8.2	8.2	8.2	85.3	57.2	54.0	27.3	31.5	86.7	99.5
PriorNet	28.1	0.8	0.3	0.4	1.6	8.4	26.8	28.1	2.5	0.7	0.2	2.3	18.9	41.0
DDNet	21.0	3.0	0.9	0.4	0.6	2.1	7.3	21.0	4.4	2.1	1.9	2.2	2.2	4.1
EvNet	74.2	21.4	12.2	4.3	1.4	0.6	0.3	74.2	45.3	38.5	19.6	9.6	12.1	26.0
Seg. – Seg. class sky														
PostNet	99.2	84.7	55.5	23.0	9.7	4.4	4.7	99.2	92.1	77.1	41.5	24.9	41.0	80.8
PriorNet	17.1	4.4	1.3	0.0	0.0	0.0	0.1	17.1	5.9	1.5	0.1	0.0	0.1	5.8
DDNet	4.1	1.1	0.0	0.0	0.0	0.0	0.0	4.1	1.8	0.4	0.0	0.0	0.0	0.0
EvNet	91.2	54.5	23.3	3.9	0.9	0.4	0.2	91.2	82.9	76.4	42.2	9.7	0.8	0.6

6.4. How to make DBU models more robust

To improve robustness of DBU models we perform median smoothing and adversarial training. Smoothing computes the smooth median, worst case and best case performance of DBU models for three tasks: distinguishing between correct and wrong predictions, attack detection, distinguishing between ID data and OOD data under label attacks and under uncertainty attacks.

Table 46. OOD detection based on differential entropy under PGD uncertainty attacks against differential entropy on ID data and OOD data. Smoothed DBU models on MNIST. Column format: guaranteed lowest performance · empirical performance · guaranteed highest performance (blue: normally/adversarially trained smooth classifier is more robust than the base model).

	Att. Rad.	0.0	0.1	0.2	0.5	1.0	2.0
ID-Attack							
Smoothed models	PostNet	59.9 · 91.1 · 98.6	61.2 · 97.7 · 99.6	64.8 · 94.7 · 99.7	31.6 · 64.9 · 99.7	30.7 · 63.2 · 100.0	30.7 · 70.5 · 100.0
	PriorNet	99.8 · 99.8 · 99.8	99.4 · 99.8 · 99.9	98.3 · 99.6 · 99.9	48.5 · 91.9 · 99.9	31.1 · 74.6 · 99.8	30.7 · 67.3 · 100.0
	DDNet	98.5 · 98.6 · 98.7	95.0 · 97.6 · 98.9	74.7 · 92.0 · 98.2	31.4 · 52.0 · 98.5	30.7 · 52.0 · 100.0	30.7 · 41.1 · 100.0
	EvNet	85.7 · 87.5 · 89.2	68.9 · 90.4 · 97.7	42.5 · 90.2 · 99.6	30.7 · 69.8 · 100.0	30.7 · 50.3 · 100.0	30.7 · 45.6 · 100.0
Smoothed + adv. w. label attacks	PostNet	-	84.3 · 96.2 · 99.3	50.4 · 89.2 · 99.5	30.9 · 46.2 · 99.4	30.7 · 46.9 · 100.0	30.7 · 62.2 · 100.0
	PriorNet	-	99.7 · 99.9 · 100.0	98.7 · 99.8 · 100.0	83.3 · 99.1 · 100.0	30.7 · 82.6 · 100.0	30.7 · 64.8 · 100.0
	DDNet	-	93.6 · 96.9 · 98.5	71.2 · 89.1 · 96.9	32.3 · 50.3 · 99.0	30.7 · 50.7 · 100.0	30.7 · 55.7 · 100.0
	EvNet	-	58.2 · 84.4 · 94.3	40.9 · 87.4 · 99.2	30.7 · 59.4 · 100.0	30.7 · 40.3 · 100.0	30.7 · 53.2 · 100.0
Smoothed + adv. w. uncert. attacks	PostNet	-	58.9 · 96.1 · 99.3	59.7 · 96.1 · 99.9	31.2 · 48.2 · 95.7	30.7 · 42.0 · 100.0	30.7 · 56.9 · 100.0
	PriorNet	-	99.9 · 100.0 · 100.0	96.5 · 99.2 · 99.9	49.2 · 96.9 · 100.0	31.3 · 88.1 · 100.0	30.7 · 77.8 · 100.0
	DDNet	-	95.0 · 97.5 · 98.8	80.6 · 94.1 · 98.7	31.7 · 55.6 · 98.6	30.7 · 52.0 · 100.0	30.7 · 47.6 · 100.0
	EvNet	-	66.5 · 91.3 · 98.1	48.1 · 84.1 · 97.6	30.8 · 49.7 · 99.9	30.7 · 37.9 · 100.0	30.8 · 63.5 · 100.0
OOD-Attack							
Smoothed models	PostNet	59.0 · 91.2 · 97.7	57.8 · 97.2 · 99.6	61.4 · 93.8 · 99.6	31.5 · 58.9 · 99.5	30.7 · 51.5 · 100.0	30.7 · 53.5 · 100.0
	PriorNet	99.7 · 99.8 · 99.8	99.4 · 99.8 · 99.9	98.4 · 99.7 · 100.0	60.7 · 96.8 · 100.0	33.0 · 88.9 · 100.0	30.7 · 87.7 · 100.0
	DDNet	98.4 · 98.5 · 98.7	94.2 · 97.2 · 98.7	72.1 · 90.5 · 97.8	31.6 · 52.3 · 98.1	30.7 · 51.7 · 100.0	30.7 · 37.7 · 100.0
	EvNet	83.9 · 85.7 · 88.0	63.5 · 88.6 · 97.9	40.1 · 87.7 · 99.6	30.8 · 68.9 · 100.0	30.7 · 43.3 · 100.0	30.7 · 36.8 · 100.0
Smoothed + adv. w. label attacks	PostNet	-	84.7 · 96.1 · 99.4	49.7 · 89.1 · 99.5	30.9 · 45.6 · 99.3	30.7 · 45.8 · 100.0	30.7 · 69.1 · 100.0
	PriorNet	-	99.7 · 99.9 · 100.0	98.7 · 99.8 · 100.0	86.8 · 99.5 · 100.0	30.9 · 93.2 · 100.0	30.7 · 81.4 · 100.0
	DDNet	-	93.9 · 97.0 · 98.6	72.0 · 89.4 · 97.0	33.0 · 52.4 · 98.8	30.7 · 51.5 · 100.0	30.7 · 60.1 · 100.0
	EvNet	-	59.5 · 85.3 · 94.6	40.7 · 86.9 · 99.2	30.7 · 57.4 · 100.0	30.7 · 39.2 · 100.0	30.7 · 49.0 · 100.0
Smoothed + adv. w. uncert. attacks	PostNet	-	55.7 · 96.1 · 99.3	58.4 · 95.7 · 99.8	31.1 · 44.2 · 93.1	30.7 · 41.2 · 100.0	30.7 · 48.8 · 100.0
	PriorNet	-	99.9 · 100.0 · 100.0	97.0 · 99.3 · 99.9	61.0 · 98.4 · 100.0	33.2 · 94.4 · 100.0	30.7 · 90.2 · 100.0
	DDNet	-	95.3 · 97.6 · 98.9	82.2 · 94.5 · 98.7	32.1 · 56.6 · 98.5	30.7 · 48.6 · 100.0	30.7 · 42.9 · 100.0
	EvNet	-	65.2 · 90.4 · 98.0	46.8 · 83.4 · 97.3	30.8 · 48.8 · 99.9	30.7 · 36.3 · 100.0	30.8 · 60.1 · 100.0

Table 47. OOD detection based on differential entropy under PGD uncertainty attacks against differential entropy on ID data and OOD data. Smoothed DBU models on Sensorless. Column format: guaranteed lowest performance · empirical performance · guaranteed highest performance (blue: normally/adversarially trained smooth classifier is more robust than the base model).

Att.	Rad.	0.0	0.1	0.2	0.5	1.0	2.0
ID-Attack							
Smoothed models	PostNet	49.3 · 90.4 · 99.8	30.7 · 49.2 · 100.0	30.7 · 36.0 · 100.0	49.2 · 50.0 · 74.9	50.0 · 50.0 · 50.0	50.0 · 50.0 · 50.0
	PriorNet	31.2 · 39.0 · 66.9	30.7 · 35.5 · 100.0	30.7 · 38.9 · 100.0	30.7 · 46.2 · 100.0	30.7 · 62.7 · 100.0	30.7 · 51.3 · 100.0
	DDNet	31.0 · 31.5 · 32.7	30.7 · 30.8 · 100.0	30.7 · 31.8 · 100.0	30.7 · 53.6 · 100.0	30.7 · 43.9 · 100.0	30.7 · 40.5 · 100.0
	EvNet	33.6 · 55.2 · 91.3	30.7 · 44.2 · 100.0	30.7 · 43.8 · 100.0	30.7 · 39.3 · 100.0	30.8 · 51.6 · 100.0	32.4 · 50.0 · 100.0
Smoothed + adv. w. label attacks	PostNet	-	30.7 · 62.4 · 100.0	30.7 · 39.2 · 100.0	50.0 · 50.0 · 50.0	50.0 · 50.0 · 50.0	50.0 · 50.0 · 50.0
	PriorNet	-	30.7 · 30.9 · 100.0	30.7 · 32.4 · 100.0	30.7 · 31.0 · 100.0	30.8 · 30.7 · 100.0	38.2 · 48.9 · 100.0
	DDNet	-	30.7 · 32.2 · 100.0	30.7 · 30.9 · 100.0	30.7 · 37.1 · 100.0	30.7 · 42.1 · 100.0	30.7 · 37.7 · 100.0
	EvNet	-	30.7 · 48.9 · 100.0	30.7 · 34.0 · 100.0	30.7 · 35.6 · 100.0	30.7 · 33.6 · 100.0	30.7 · 50.0 · 100.0
Smoothed + adv. w. uncert. attacks	PostNet	-	30.7 · 46.0 · 100.0	30.7 · 46.6 · 100.0	50.0 · 50.0 · 50.0	50.0 · 50.0 · 50.0	50.0 · 50.0 · 50.0
	PriorNet	-	30.7 · 35.8 · 100.0	30.7 · 32.1 · 100.0	30.7 · 81.6 · 100.0	30.8 · 41.7 · 100.0	30.7 · 61.9 · 100.0
	DDNet	-	30.7 · 32.8 · 100.0	30.7 · 31.0 · 100.0	30.7 · 31.8 · 100.0	30.7 · 43.7 · 100.0	30.7 · 34.7 · 100.0
	EvNet	-	30.7 · 31.0 · 100.0	30.7 · 49.6 · 100.0	30.7 · 47.7 · 100.0	30.7 · 42.6 · 100.0	30.7 · 50.0 · 100.0
OOD-Attack							
Smoothed models	PostNet	49.3 · 90.4 · 99.8	30.8 · 76.4 · 100.0	30.7 · 61.3 · 100.0	47.7 · 50.0 · 75.1	50.0 · 50.0 · 50.0	50.0 · 50.0 · 50.0
	PriorNet	31.2 · 39.0 · 66.9	30.7 · 33.9 · 100.0	30.7 · 34.3 · 100.0	30.7 · 37.0 · 100.0	30.7 · 74.0 · 100.0	30.9 · 78.1 · 100.0
	DDNet	31.0 · 31.5 · 32.7	30.7 · 30.7 · 100.0	30.7 · 31.8 · 100.0	30.7 · 47.7 · 100.0	30.7 · 43.8 · 100.0	30.7 · 52.5 · 100.0
	EvNet	33.6 · 55.2 · 91.2	30.7 · 54.7 · 100.0	30.7 · 54.0 · 100.0	30.7 · 51.0 · 100.0	30.7 · 45.2 · 100.0	31.7 · 50.0 · 100.0
Smoothed + adv. w. label attacks	PostNet	-	30.7 · 82.2 · 100.0	30.7 · 61.4 · 100.0	50.0 · 50.0 · 50.0	50.0 · 50.0 · 50.0	50.0 · 50.0 · 50.0
	PriorNet	-	30.7 · 31.2 · 100.0	30.7 · 31.4 · 99.9	30.7 · 30.8 · 100.0	30.8 · 30.7 · 100.0	33.8 · 34.0 · 100.0
	DDNet	-	30.7 · 32.2 · 100.0	30.7 · 30.8 · 100.0	30.7 · 33.6 · 100.0	30.7 · 46.9 · 100.0	30.7 · 40.3 · 100.0
	EvNet	-	30.8 · 75.3 · 100.0	30.7 · 31.6 · 100.0	30.7 · 42.1 · 100.0	30.7 · 38.7 · 100.0	30.7 · 50.0 · 100.0
Smoothed + adv. w. uncert. attacks	PostNet	-	30.7 · 73.7 · 100.0	30.7 · 61.6 · 100.0	50.0 · 50.0 · 50.0	50.0 · 50.0 · 50.0	50.0 · 50.0 · 50.0
	PriorNet	-	30.7 · 35.9 · 100.0	30.7 · 30.7 · 100.0	30.7 · 39.4 · 100.0	30.7 · 36.6 · 100.0	30.7 · 97.6 · 100.0
	DDNet	-	30.7 · 32.1 · 100.0	30.7 · 30.8 · 100.0	30.7 · 32.2 · 100.0	30.7 · 50.7 · 100.0	30.7 · 39.8 · 100.0
	EvNet	-	30.7 · 31.3 · 100.0	30.8 · 39.7 · 100.0	30.7 · 52.2 · 100.0	30.7 · 42.3 · 100.0	30.7 · 50.0 · 100.0

Table 48. OOD detection based on differential entropy under PGD uncertainty attacks against differential entropy on ID data and OOD data. Smoothed DBU models on Segment. Column format: guaranteed lowest performance · empirical performance · guaranteed highest performance (blue: normally/adversarially trained smooth classifier is more robust than the base model).

Att.	Rad.	0.0	0.1	0.2	0.5	1.0	2.0
ID-Attack							
Smoothed models	PostNet	99.6 · 99.9 · 99.9	33.0 · 83.0 · 100.0	30.8 · 43.8 · 100.0	30.8 · 31.7 · 100.0	30.8 · 40.8 · 100.0	41.4 · 50.0 · 50.2
	PriorNet	30.8 · 31.0 · 31.4	30.8 · 30.8 · 42.6	30.8 · 30.8 · 95.5	30.8 · 33.1 · 100.0	30.8 · 76.4 · 100.0	30.8 · 78.7 · 100.0
	DDNet	30.8 · 30.8 · 30.8	30.8 · 30.8 · 32.1	30.8 · 30.8 · 69.4	30.8 · 30.8 · 100.0	30.8 · 31.0 · 100.0	30.8 · 33.4 · 100.0
	EvNet	94.9 · 97.2 · 98.3	31.1 · 75.8 · 99.9	30.8 · 74.2 · 100.0	30.8 · 62.9 · 100.0	30.8 · 58.1 · 100.0	30.8 · 43.4 · 100.0
Smoothed + adv. w. label attacks	PostNet	-	31.0 · 70.9 · 100.0	30.8 · 47.1 · 100.0	30.8 · 85.0 · 100.0	30.8 · 50.0 · 100.0	50.0 · 50.0 · 50.0
	PriorNet	-	30.8 · 30.8 · 46.0	30.8 · 30.8 · 32.7	30.8 · 30.8 · 100.0	30.8 · 30.8 · 100.0	30.9 · 30.8 · 100.0
	DDNet	-	30.8 · 30.8 · 30.8	30.8 · 30.8 · 79.5	30.8 · 30.8 · 100.0	30.8 · 30.8 · 100.0	30.8 · 57.3 · 100.0
	EvNet	-	36.3 · 94.3 · 100.0	30.8 · 32.2 · 100.0	30.8 · 50.2 · 100.0	30.8 · 93.9 · 100.0	30.8 · 56.3 · 100.0
Smoothed + adv. w. uncert. attacks	PostNet	-	30.8 · 49.5 · 100.0	30.8 · 34.5 · 100.0	30.8 · 96.1 · 100.0	41.2 · 50.0 · 82.7	50.0 · 50.0 · 50.0
	PriorNet	-	30.8 · 31.2 · 62.6	30.8 · 30.8 · 32.9	30.8 · 30.8 · 88.9	30.8 · 30.8 · 100.0	30.8 · 30.8 · 100.0
	DDNet	-	30.8 · 30.8 · 31.2	30.8 · 30.8 · 68.9	30.8 · 30.8 · 100.0	30.8 · 30.9 · 100.0	30.8 · 38.6 · 100.0
	EvNet	-	30.9 · 83.5 · 100.0	30.8 · 84.0 · 100.0	30.8 · 98.6 · 100.0	30.8 · 92.8 · 100.0	30.8 · 45.6 · 100.0
OOD-Attack							
Smoothed models	PostNet	99.6 · 99.9 · 99.9	31.3 · 95.2 · 100.0	30.8 · 48.7 · 100.0	30.8 · 34.0 · 100.0	30.8 · 41.0 · 100.0	41.8 · 50.0 · 50.2
	PriorNet	30.8 · 31.0 · 31.4	30.8 · 30.8 · 44.7	30.8 · 30.8 · 86.3	30.8 · 30.9 · 100.0	30.8 · 35.7 · 100.0	30.8 · 57.4 · 100.0
	DDNet	30.8 · 30.8 · 30.8	30.8 · 30.8 · 31.9	30.8 · 30.8 · 58.3	30.8 · 30.8 · 100.0	30.8 · 30.8 · 100.0	30.8 · 30.8 · 100.0
	EvNet	94.9 · 97.2 · 98.3	31.4 · 92.5 · 100.0	30.8 · 94.2 · 100.0	30.8 · 80.4 · 100.0	30.8 · 70.2 · 100.0	30.8 · 48.2 · 100.0
Smoothed + adv. w. label attacks	PostNet	-	30.8 · 88.7 · 100.0	30.8 · 70.9 · 100.0	30.8 · 97.2 · 100.0	30.8 · 50.0 · 100.0	50.0 · 50.0 · 50.0
	PriorNet	-	30.8 · 30.9 · 47.2	30.8 · 30.8 · 32.5	30.8 · 30.8 · 96.2	30.8 · 30.8 · 100.0	30.9 · 30.8 · 100.0
	DDNet	-	30.8 · 30.8 · 30.8	30.8 · 30.8 · 73.5	30.8 · 30.8 · 100.0	30.8 · 30.8 · 100.0	30.8 · 34.3 · 100.0
	EvNet	-	35.9 · 95.9 · 100.0	30.8 · 36.6 · 100.0	30.8 · 45.8 · 100.0	30.8 · 75.2 · 100.0	30.8 · 93.8 · 100.0
Smoothed + adv. w. uncert. attacks	PostNet	-	30.8 · 64.6 · 100.0	30.8 · 31.9 · 100.0	30.8 · 99.1 · 100.0	37.2 · 50.0 · 100.0	49.8 · 50.0 · 50.0
	PriorNet	-	30.8 · 31.3 · 60.6	30.8 · 30.8 · 34.8	30.8 · 30.8 · 73.8	30.8 · 30.8 · 100.0	30.8 · 30.8 · 100.0
	DDNet	-	30.8 · 30.8 · 31.7	30.8 · 30.8 · 64.6	30.8 · 30.8 · 100.0	30.8 · 30.8 · 100.0	30.8 · 30.8 · 100.0
	EvNet	-	31.1 · 90.7 · 100.0	30.8 · 96.6 · 100.0	30.8 · 98.9 · 100.0	30.8 · 97.5 · 100.0	30.8 · 34.2 · 100.0

6.5. Visualization of differential entropy distributions on ID data and OOD data

The following Figures visualize the differential entropy distribution for ID data and OOD data for all models with standard training. We used label attacks and uncertainty attacks for CIFAR10 and MNIST. Thus, they show how well the DBU models separate on clean and perturbed ID data and OOD data.

Figures 4 and 5 visualizes the differential entropy distribution of ID data and OOD data under label attacks. On CIFAR10, PriorNet and DDNet can barely distinguish between clean ID and OOD data. We observe a better ID/OOD distinction for PostNet and EvNet for clean data. However, we do not observe for any model an increase of the uncertainty estimates on label attacked data. Even worse, PostNet, PriorNet and DDNet seem to assign higher confidence on class label attacks. On MNIST, models show a slightly better behavior. They are capable to assign a higher uncertainty to label attacks up to some attack radius.

Figures 6, 7, 8 and 9 visualizes the differential entropy distribution of ID data and OOD data under uncertainty attacks. For both CIFAR10 and MNIST data sets, we observed that uncertainty estimations of all models can be manipulated. That is, OOD uncertainty attacks can shift the OOD uncertainty distribution to more certain predictions, and ID uncertainty attacks can shift the ID uncertainty distribution to less certain predictions.

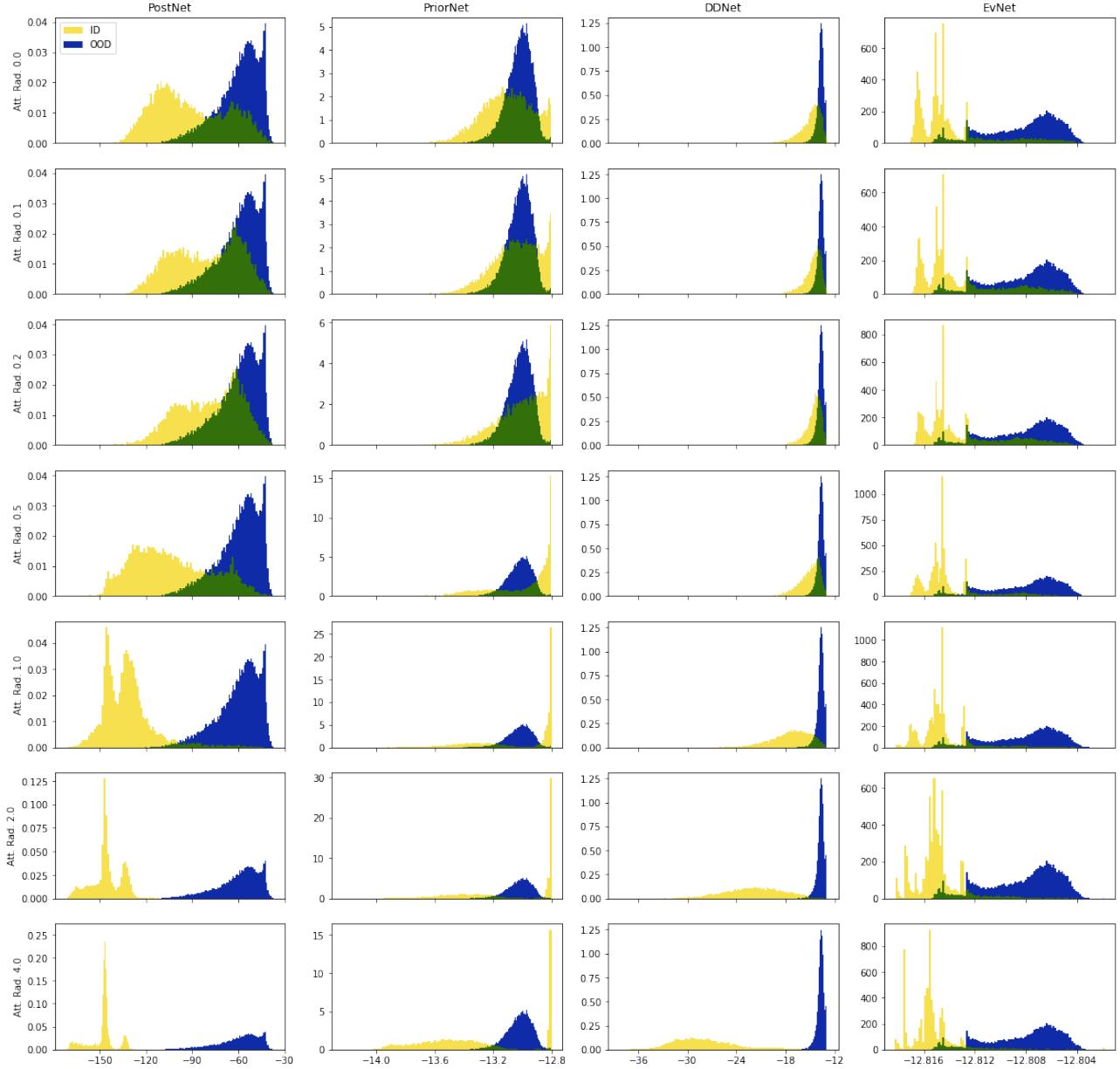


Figure 4. Visualization of the differential entropy distribution of ID data (CIFAR10) and OOD data (SVHN) under label attack. The first row corresponds to no attack. The other rows correspond do increasingly stronger attack strength.

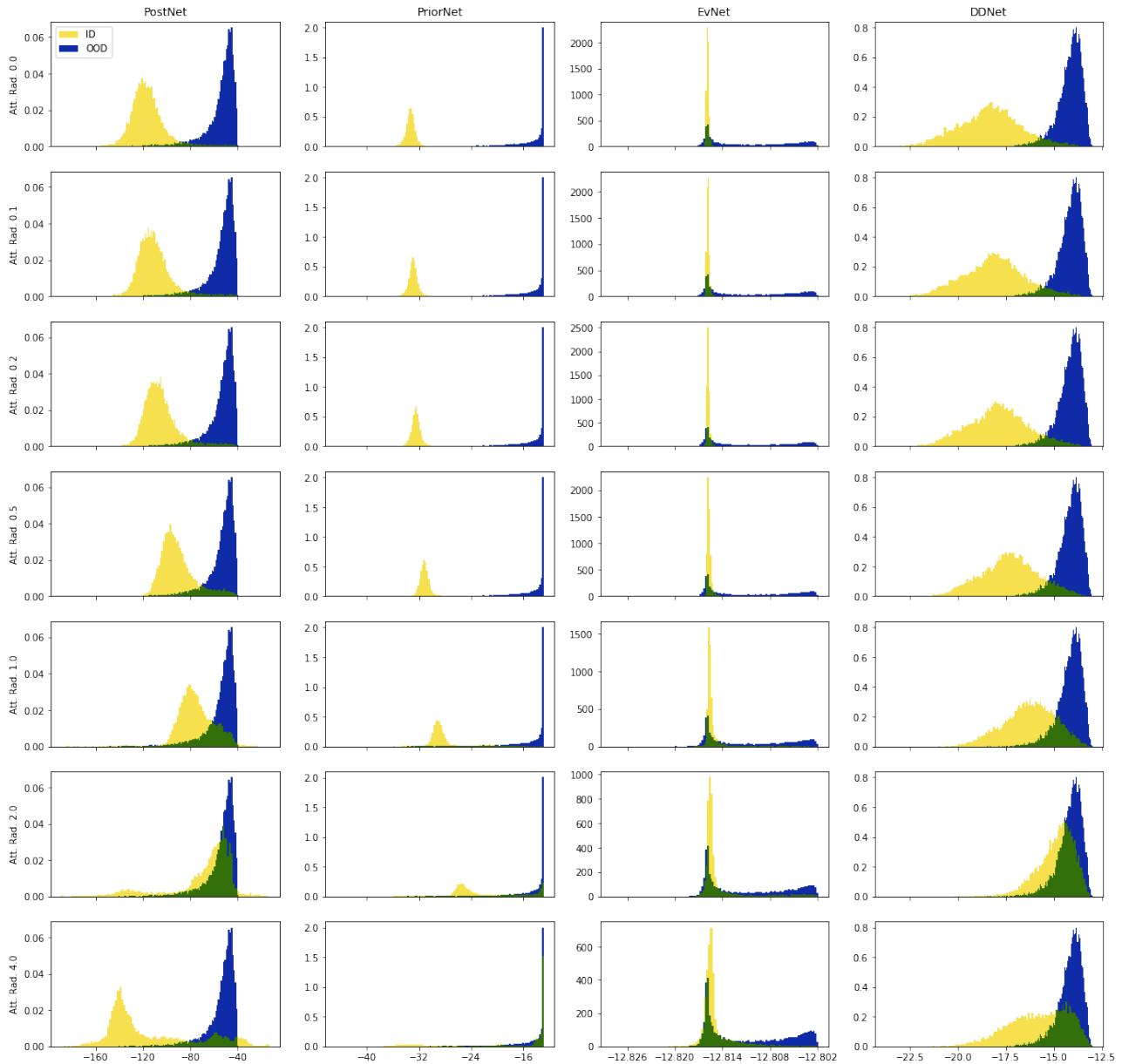


Figure 5. Visualization of the differential entropy distribution of ID data (MNIST) and OOD data (KMNIST) under label attack. The first row corresponds to no attack. The other rows correspond do increasingly stronger attack strength.

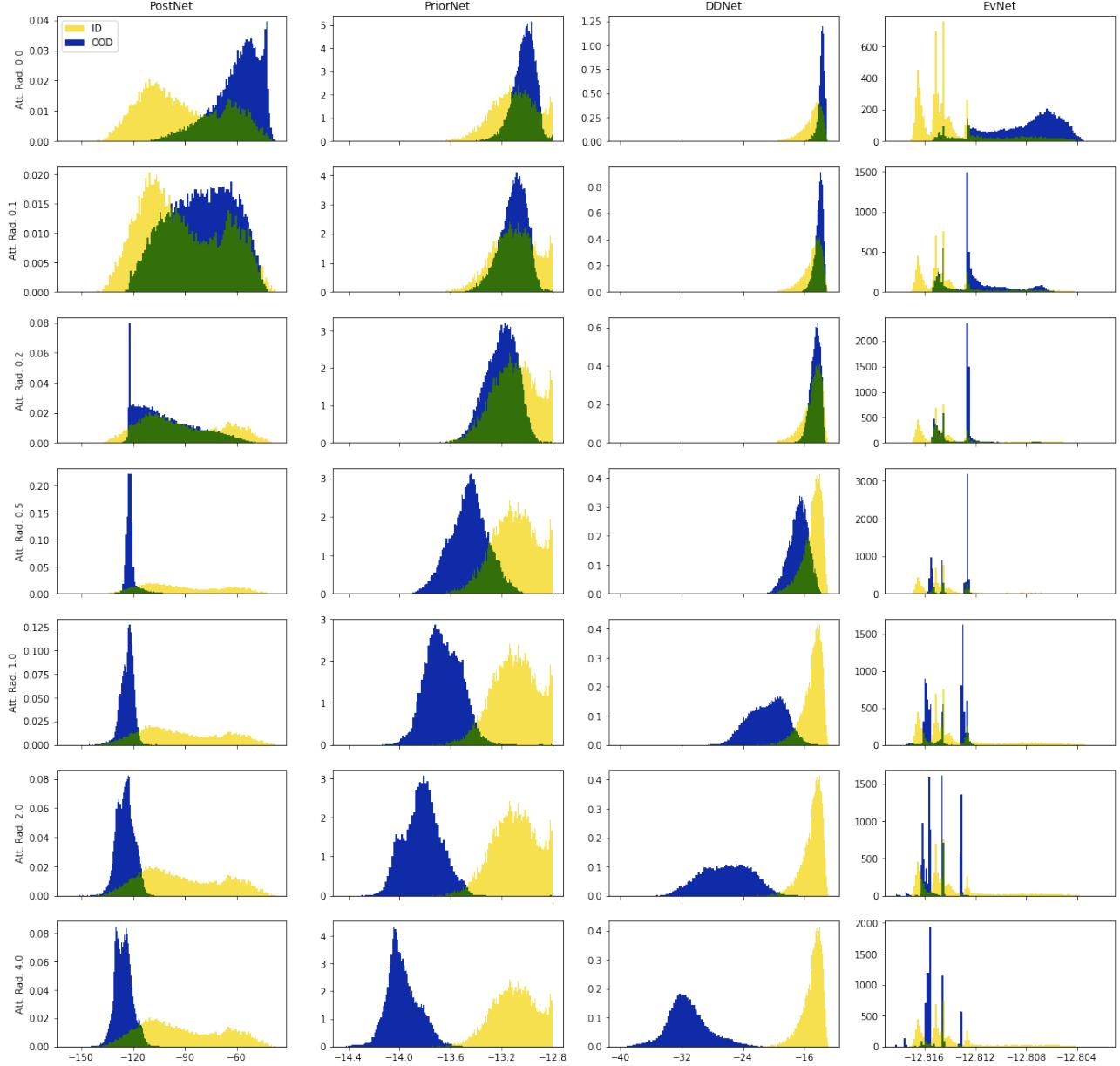


Figure 6. Visualization of the differential entropy distribution of ID data (CIFAR10) and OOD data (SVHN) under OOD uncertainty attack. The first row corresponds to no attack. The other rows correspond do increasingly stronger attack strength.

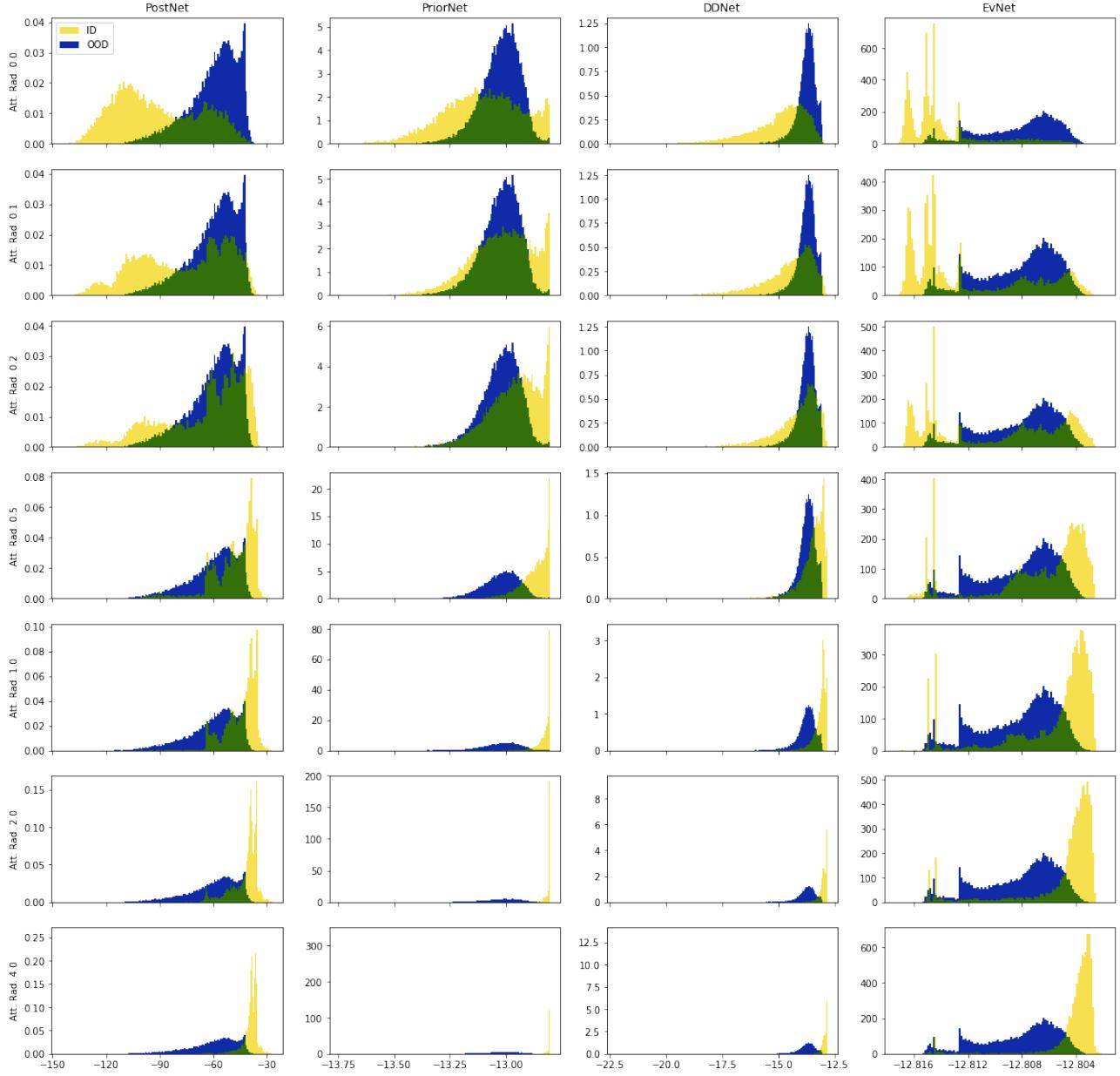


Figure 7. Visualization of the differential entropy distribution of ID data (CIFAR10) and OOD data (SVHN) under ID uncertainty attack. The first row corresponds to no attack. The other rows correspond to increasingly stronger attack strength.

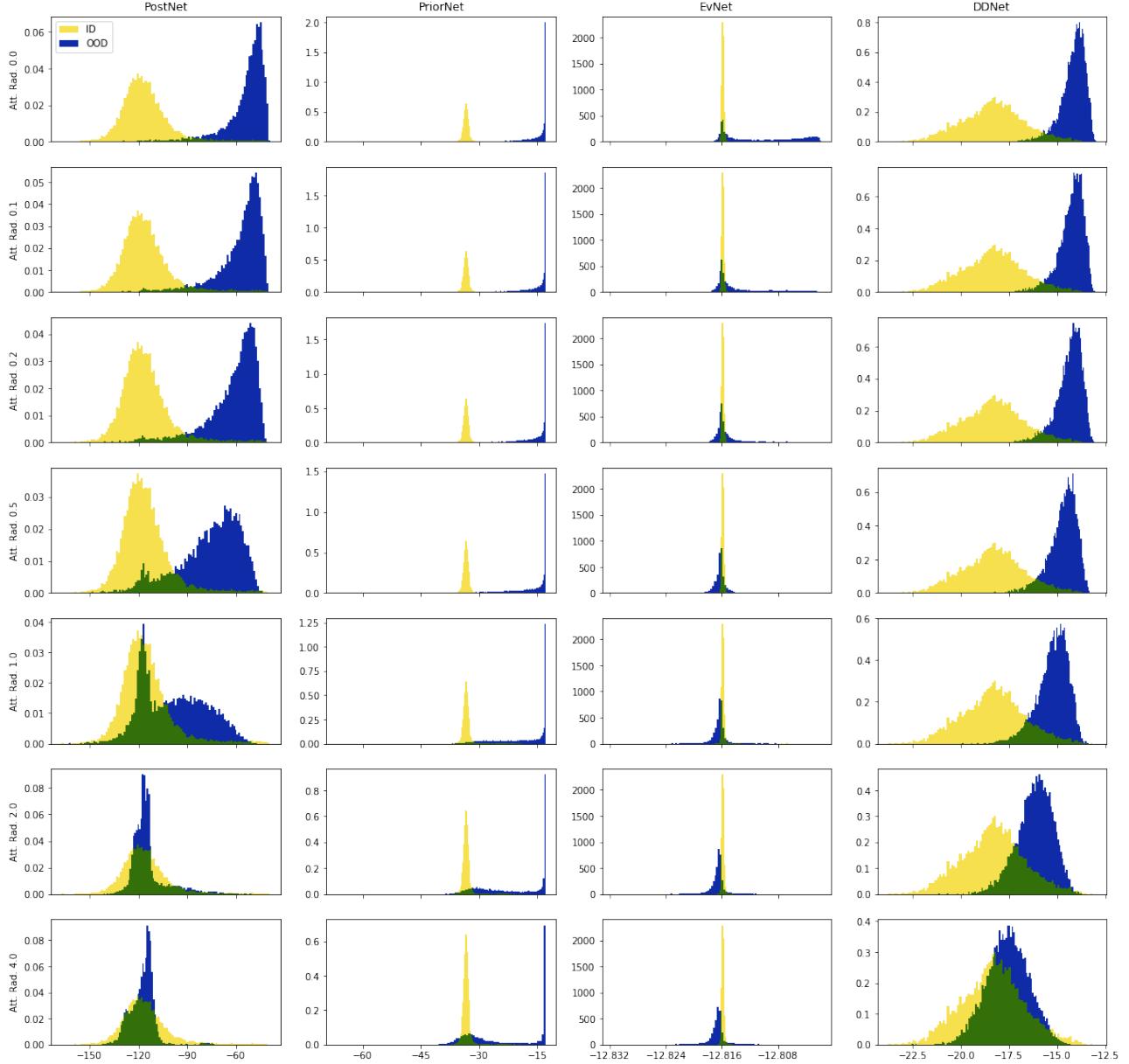


Figure 8. Visualization of the differential entropy distribution of ID data (MNIST) and OOD data (KMNIST) under OOD uncertainty attack. The first row corresponds to no attack. The other rows correspond do increasingly stronger attack strength.

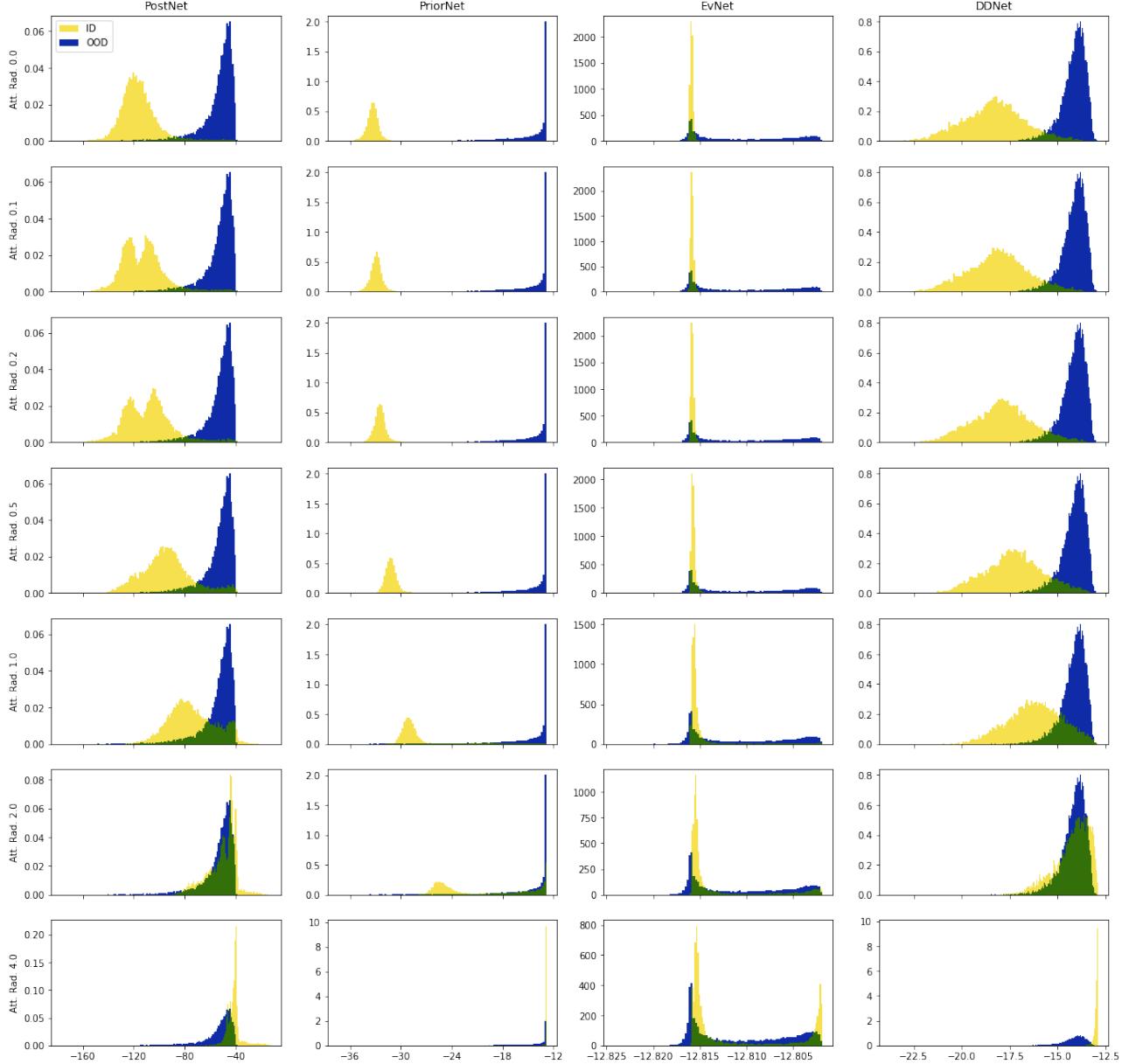


Figure 9. Visualization of the differential entropy distribution of ID data (MNIST) and OOD data (KMNIST) under ID uncertainty attack. The first row corresponds to no attack. The other rows correspond do increasingly stronger attack strength.